LA-UR-02-2173

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Title:

NONDESTRUCTIVE, IN-PROCESS INSPECTION OF INERTIA FRICTION WELDING: AN INVESTIGATION INTO A NEW SENSING TECHNIQUE

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Submitted to:

6th International Conference on Trends in Welding Research
April 15-19, 2002
Callaway Gardens Resort
Pine Mountain, Georgia, USA

Los Alamos
NATIONAL LABORATORY

Nondestructive, In-Process Inspection of Inertia Friction Welding: An Investigation into a New Sensing Technique

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Abstract.

This paper investigates the capabilities of a new sensor for in-process monitoring of quality during friction welding. The non-contact sensor is composed of microphones that are mounted in an aluminum ring which surrounds the weld joint. The sensor collects the acoustical energy (in the form of sound pressure) that is emitted during the plastic deformation and phase transformations (if applicable) in friction welding processes.

The focus in this preliminary investigation is to search for and identify features within the acoustical emission that are indicative of bond quality. Bar-to-bar inertia friction welding (one form of friction welding) of copper to 304L stainless steel is used in this proof-of-concept study. This material combination exhibits only marginal weldability and is ideally suited for validating the capabilities of this new sensing technique.

A probabilistic neural network is employed in this work to analyze the acoustical emission's frequency spectrum in an attempt to classify acceptable, conditional, and unacceptable welds. Our preliminary findings indicate that quality-based process features do exist within the frequency spectrum of the acoustical signature. The results from this analysis are presented. Future work in improving the sensing and interpretation of the data is discussed in an effort to develop a robust method of quality-based, in-process monitoring of friction welds.

INTRODUCTION

Traditionally, critical inertia-friction welded joints tend to be difficult to inspect for two reasons: (1) non-destructive evaluation techniques only detect gross disbonds leaving more subtle discontinuities which could have a significant effect on fatigue life or joint fracture toughness; and (2) destructive post-process inspection is time-consuming and costly for highly man-rated applications.

Although improvements in post-process, nondestructive tests have been realized in R&D laboratory environments [1], no reliable method is available for detecting in-situ weld quality in a production environment. For commercial applications, weld parameter development and post-process inspection efforts can result in up to a 200%-time (and cost) overhead in the overall manufacturing process with little value added [2]. Therefore, manufacturers interested in reducing costs and increasing quality should consider an in-process means of determining part quality.

A vein of noteworthy research into in-process quality detection of friction welds has been pursued by Wang and Oh. In [3], Wang, et al. demonstrated the feasibility of using acoustical emission (AE) as an in-process quality metric for inertia friction welding (IFRW) of ferrous metals. The authors were able to correlate AE counts to joint strength for bar-to-bar (AISI 4140 to 1117 and 12L14) and tube-to-tube (AISI 1020 to 304SS) welds. AE sensing was accomplished with a piezoelectric transducer attached directly to either the stationary chuck or the workpiece. For mild steels, the authors found two distinctive regions of AE: one during the welding process (A-zone) and the other during the cool-down portion of the weld cycle (B-zone). The first burst of AE activity is due primarily to the plastic deformation of the material during the weld, whereas the second burst of AE activity is suspected to be a result of martensitic transformation. The authors showed relatively good correlation between the cumulative B-zone AE counts and the tensile breaking force (i.e., strength) for ferrous metals. However, their non-ferrous (aluminum and copper) metal experiments resulted in no detectable B-zone AE activities, and hence they were unable to determine weld strength.

Oh, et al. [4, 5] extended the data analysis portion of the experimental work conducted by Wang, et al. [3]. The authors used the total cumulative AE counts (i.e., A-zone counts + B-zone counts) as an in-process quality metric. In particular, they were able to correlate weld strength with (1) total cumulative AE counts and initial energy, (2) total cumulative AE counts and total upset, and (3) total cumulative AE counts and welding time (for continuous drive friction welding). The authors were able to empirically derive an equation for tensile strength that can be used for in-process monitoring and control of friction weld strength. In [6], Oh, et al. correlated weld strength to IFRW welding parameters (rotational speed, pressure, and inertia) and total cumulative AE counts. Oh, et al. presented their final report [7] that correlates Zone-A AE counts and weld strength.

The current industry approach to ensuring quality in IFRW

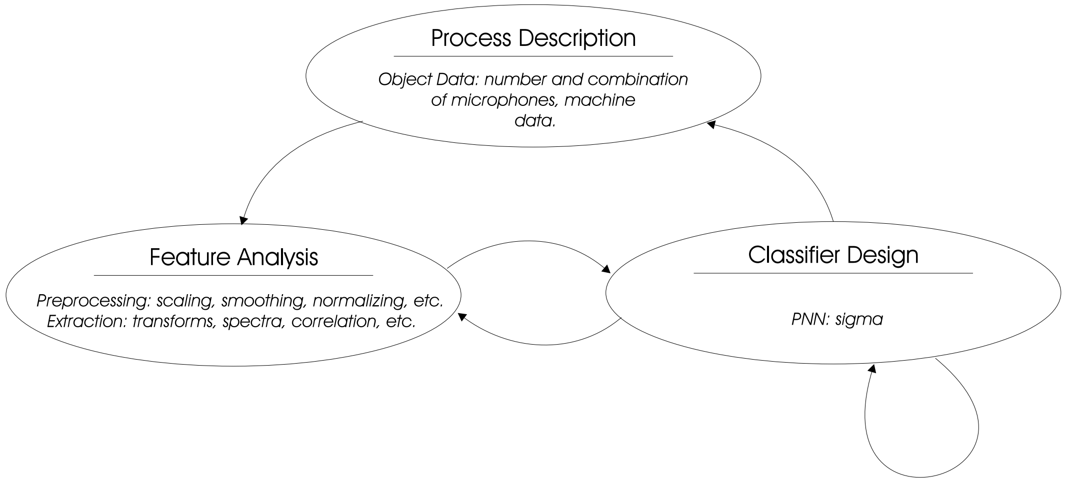

FIGURE 1. Pattern classification system.

relies upon maintaining absolute upset within a predetermined $\pm3\sigma$ envelope and applies this quality metric post-process. Previous work by Hartman, et al. [8] demonstrated that this technique is capable of detecting faulty welds when machine parameters varied slightly from their nominal. However, other defect conditions, such as, surface contamination and misalignment, were not detectable by monitoring absolute upset.

An investigation into the feasibility of using a new, non-contact acoustical sensing technique is presented. In particular, the AE data from this sensor will be analyzed using a neural network pattern classification system in order to determine if information exists within the data that can be correlated to bond quality. The Pattern Recognition Section provides an overview of and the method used for building a pattern recognition system. The next two sections (Experimental Approach and Results and Discussion) discuss the methods used and the results achieved for this exploratory work. Finally, a Conclusions and Future Work Section summarizes our findings and presents several research directions in which to extend this work.

PATTERN RECOGNITION

Duda and Hart [9] define pattern recognition as the "machine recognition of meaningful regularities in noisy or complex environments". Bezdek [10] provides the following definition: "pattern recognition is the search for structure in data." The goal in this research is to identify features within the acoustical signature of an inertia-friction weld that quantifies its bond quality. At this stage of the research, we are only interested in identifying the difference between acceptable and unacceptable bond quality. This type of categorical identification is commonly referred to as pattern classification.

Pattern classification is only one of several forms of pattern recognition. Other commonly applied pattern recognition techniques include estimation, prediction, and control. The development of a successful pattern classification system[1] for this research involved iteratively revisiting the three modules shown in Figure 1 until the system (1) satisfied a given set of performance requirements and economic constraints or (2) failed to yield any acceptable results[2]. The arrows in Figure 1 represent modifications to a module which results in re-evaluating the classifier's performance.

The process description for this research was captured with machine process data (speed, pressure, and upset) and acoustical energy. In [8], Hartman, et al. demonstrated the ability to detect and classify various defective conditions in similar material, tubular inertia-friction welds using only machine process data. The dissimilar welds produced in this research are an order of magnitude more difficult to weld, and it was therefore determined that an in-process monitoring technique would need additional sensing mechanisms. The work performed by Wang and Oh encouraged the authors to pursue a similar sensing method.

Defining the process description, by determining what combination of sensing data would yield classifiable features, was one aspect of the iterative nature of this pattern classification effort. Once the process description is determined, the next step is feature analysis. Feature analysis represents techniques that explore and improve upon "raw" data. Two methods of feature analysis that were used in this research were preprocessing (scaling, smoothing, interpolating, and normalizing) and extracting (discrete Fourier transform and spectrogram). Therefore, the second iterative nature of this effort was determining the most effective feature analysis method(s).

Classifier design represents the third module of this pattern classification system and the ultimate goal: to find a partition within the process description data that yields a computationally

[1] The method presented in this paper is modified from a methodology presented by Bezdek in [11].

[2] The authors were uncertain if the acoustical energy collected by a ring of microphones would yield any process specific information that could be correlated to quality.

explicit (e.g., discriminant functions, nearest prototype rules) or implicit (e.g., multilayered Perceptrons, k-nearest neighbor rules) decision function. A supervised classifier design using a PNN was chosen because of its successful application in [8]. The smoothing parameter, σ, is the only parameter affecting the performance of a basic PNN and, therefore, represents the third iterative aspect of this classification problem.

EXPERIMENTAL APPROACH

An experimental matrix was devised that could provide a relatively straight-forward method of evaluating the merits of this new sensing technique. Therefore, the goal for the experimental matrix was to generate two types of welds: acceptable and unacceptable. An acceptable weld is defined as one in which the majority of the interfacing surfaces are bonded. An unacceptable weld is defined as one in which no or little bonding at the surfaces exists. The rest of this section will detail each component of the experimental approach.

Materials and Preparation

Throughout this study oxygen-free, high-conductivity (OFHC) copper bar nominally 1-inch diameter and annealed Type 304L stainless steel bar nominally 0.5-inch diameter were used. OFHC copper is essentially 99.99 percent pure, while 304L is a low carbon grade of austenitic stainless steel. About three weeks before welding each specimen was given a preliminary machining step to ensure a faying surface finish of 32 μin.

Welding Procedure

All welding was conducted using an MTI Model 90B inertia friction welding system. Initial parameter selection was based upon work by Bell et al. [18] but altered slightly to accommodate differences in available inertial mass. The welding parameters remained constant throughout this investigation and are listed in Table 1. Selected copper specimens were machined immediately before welding while bathed in isopropyl alcohol. Others were welded as-is, i.e., without further machining to remove surface oxidation that might have occurred while at ambient temperature and pressure for up to five weeks prior to welding. In all cases, the stainless steel was rotated during the weld cycle while the copper remained fixed. Lastly, the specimens extended from the spindle and fixture collets by approximately one diameter.

Acoustical Sensing and Data Collection

A non-contact array of microphones which surround the weld joint was used to collect the rapid release of energy (sound pressure) due to the mechanical, thermal, and metallurgical phenomenon occurring during friction welding. The acoustical transducers used in this research are off-the-shelf electret condenser microphones.

The non-contact sensing ring accurately measures sound pressures at audio frequencies in the air. Up to twelve (12) microphones can be held in the aluminum ring. Figure 2 illustrates our experimental setup in which four microphones are evenly placed around the ring.

The acoustical data was sampled at 40 kHz per channel. Calibration of the microphones was accomplished by comparing it to a calibrated Brüel & Kjær condenser microphone, type 4133, within the frequency sensitivity range of the sensor's microphones.

Microstructural Characterization

Standard metallographic procedures were used to prepare selected specimens to a 1 μm finish. Microstructural features were revealed by using a double etching procedure comprising a 5% ammonium persulphate etch for the OFHC copper followed by an electrolytic 10% oxalic acid etch for the stainless steel. Light microscopy up to 100X magnification revealed salient features of the bond interface and surrounding heat and deformation zone (HDZ).

TABLE 1. Welding parameters.

Parameter	Setting	
Inertial mass	1.52	$lb_f \cdot ft^2$
Rotational speed	4500	rpm
Surface velocity*	589	$sfpm$
Axial force	7100	lb_f
Weld pressure†	1092	psi
Weld energy‡	5241	$ft \cdot lb_f$
Prebond gap	0.100	in
Dwell time	3	sec
Average upset	0.150	in

* For 0.5 inch diameter bar
† Ram area = 4.9 in^2
‡ Energy = $(wk^2 \times rpm^2)/5873$

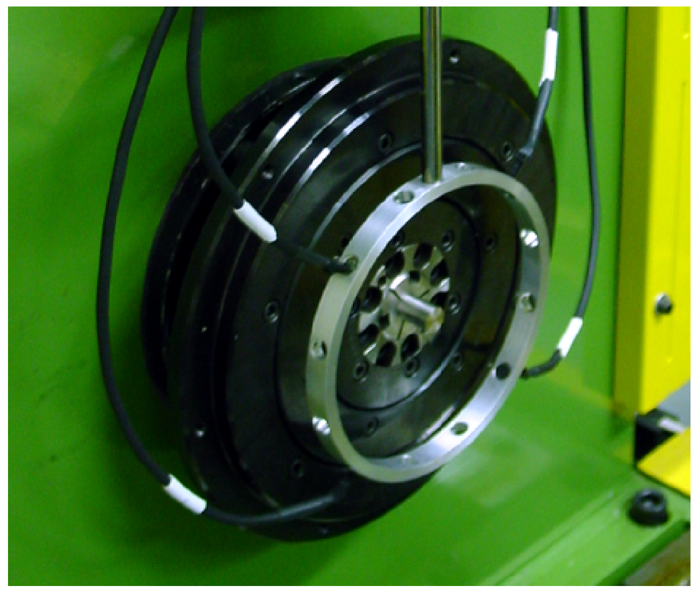

FIGURE 2. Acoustic ring assembly with four (4) microphones.

TABLE 2. Variables that were modified during the development of the pattern recognition system.

Module	*Variable*	*Possible Values*
Process Description	microphones	1 1 & 3 2 & 4 1, 2, 3, & 4
Feature Analysis	window position	0 – 120,000
Feature Analysis	FFT size	1024 2048 4096 8192 16384

Mechanical Testing

A semi-quantitative evaluation of each joint was performed using unguided bend testing. As-welded, full-size specimens were tested. Image analysis techniques were used to determine the percent of bonded area after fracturing each specimen.

Classifying Bond Quality

A probabilistic neural network[3] (PNN) was used as the classifier for this work. A PNN's unique architecture and training method provide the following benefits:

- A PNN can begin classifying after having just one training pattern from each category.
- A PNN is orders of magnitude faster to train than a traditional backpropagation neural network.
- A PNN can be shown to asymptotically approach Bayes' optimal decision surface without the possibility of getting stuck in local minima.
- A PNN architecture is conducive to enabling a human to understand how the network works.

A PNN is therefore ideal for exploring data sets in which the structure is ill-defined and that contain both deterministic and random signals.

A series of neural network trainings and trials was performed in an effort to search for features that could be used to correlate the AE data to bond quality. As described earlier in the Pattern Recognition Section and illustrated in Figure 1, any modifications to either the process description, feature analysis, or classifier design resulted in re-running the system and evaluating its performance. The variables listed in Table 2 were modified during the iterative development of the pattern recognition system.

Three different classifications were investigated: (1) acceptable and unacceptable, (2) acceptable and conditional, and (3) acceptable, conditional, and unacceptable. A moving window discrete Fourier transform (DFT) was performed on the AE data using the fast Fourier transform (FFT) algorithm. A step size of 250 data points was used to move through the time-domain data (120,000 samples ⇔ 3 seconds at 40 kHz) without overlap.

Each segment of the time-domain data was filtered using a Hanning Window and then transformed into the frequency domain. Finally, the transformed data was then normalized prior to including it in the training patterns for the PNN. For multiple microphones, the normalized and transformed data was appended to the other microphone's transforms before including it in the training patterns.

Each window increment within the signal resulted in a complete training and testing of the PNN's ability to classify bond quality. Training consisted of (1) removing one pattern from the training data, (2) training the PNN, and (3) testing the PNN with the removed pattern. This was repeated for each pattern within the set. The PNN's accuracy in classifying bond quality was then determined by summing the total number of correct classifications and dividing by the total number of training patterns.

The result of this training and testing phase will yield a classification accuracy vs. time plot. This plot will identify the location of features within the acoustical signature that can be used to infer bond quality. Once this is determined, future work can improve upon the process description, feature analysis, and classifier design in an effort to build a robust, in-process monitoring system for inertia friction welding and, potentially, for other friction welding processes.

RESULTS AND DISCUSSION

Although the experimental matrix was designed with only one variable in mind (surface preparation of the copper), three different quality welds were generated:

- Acceptable: bonded area is approximately 100%.
- Conditional: bonded area is less than 100% but greater than 5%.
- Unacceptable: bonded area is less than 5%.

The conditional welds were prepared in the same manner as the acceptable welds (see Table 3) which demonstrates the difficult nature of joining these two materials.

Visual Examination

After welding, each specimen was visually inspected for uniformity and color of weld flash. Figure 3 illustrates a typical flash and fracture surface for each category of weld. All specimens exhibited a symmetric flash with a light golden color. Moreover, the amount of upset (or reduction in length [RIL]) was approximately equal and predominately occurred in the copper. Moreover, the fact that the RIL's were approximately equal, yet acceptable, conditional, and unacceptable welds resulted, suggests that RIL alone is an insufficient measure of bond quality (see Table 3).

Microstructural Observations

Specimens that were machined immediately before welding exhibited a copper-side HDZ that was uniform across the diameter – as expected. This type of HDZ shape indicates that the part's

[3] For more information on the architecture and implementation of a PNN see [12, 13].

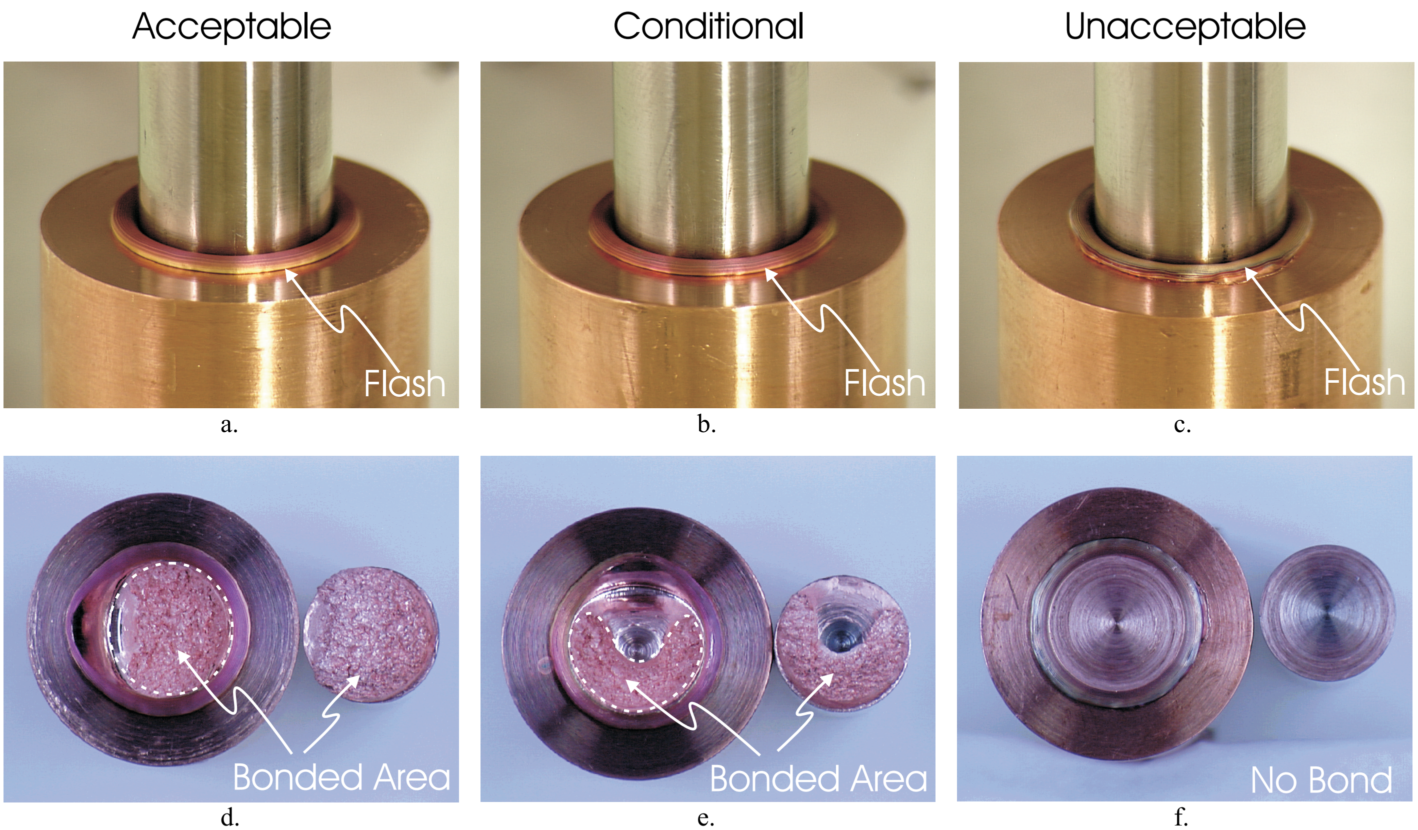

FIGURE 3. Typical weld flash and fracture surfaces for acceptable, conditional and unacceptable welds.

speed was at least sufficient to ensure center heating. Specimens that were welded as-is had a HDZ shape that was narrowest at the center indicating insufficient heat generation not from lack of speed since all parameters remained constant, but rather due to insufficient oxide removal during the upset/forging phase. The microstructural features observed on each side of the joint interface were as expected given the large difference in yield strength between the copper and stainless steel. At high magnification, the interface of a typical as-welded specimen exhibited no apparent discontinuities or lack of bonding. However, the refined grain size on the copper side of the interface is readily distinguishable from the stainless steel where a very narrow band (approximately 5 μm) of deformation appears immediately adjacent to the interface.

Mechanical Properties

Qualitative bond area from unguided bend test results are summarized in Table 3 and illustrated in Figure 3. Because the actual force required for failure was not measured, the test results are semi-quantitative at best. Nonetheless, sufficient information exists to render a determination of acceptable bond quality based on fracture surface morphology and percent of interface area bonded. Image analysis of the fracture surfaces provided a reasonable approximation of the percent of interface area bonded for specimens exhibiting less than 100% bonding. Specimens having acceptable bond quality exhibited ductile tearing through the copper without any lack of bonding (see Figure 3). However, all of the specimens that were welded as-is, i.e., not freshly machined, exhibited a lack of bonding over the majority of the interface. Generally, the as-welded specimens exhibited little to no ductile features on the fracture surfaces. Lastly, there are those specimens that exhibited conditional bond quality and are order ranked between acceptable and unacceptable (see Table 3).

TABLE 3. Bend test results.

Weld Number	Surface Condition Before Welding	Bond Quality	Bonded Area (%)
1 - 12	Freshly Machined	Acceptable	100.0
13	Freshly Machined	Conditional	80.0
14	Freshly Machined	Conditional	70.0
15	Freshly Machined	Conditional	69.0
16	Freshly Machined	Conditional	67.0
17	Freshly Machined	Conditional	54.0
18	Freshly Machined	Conditional	26.0
19 - 23	Not Machined	Unacceptable	0.0

Classification

Figure 4 illustrates the most promising results from this exploratory study. It was found that four microphones yielded improved accuracy over one microphone and was comparable to or better than two microphones. The results, however, were not as conclusive in terms of FFT size.

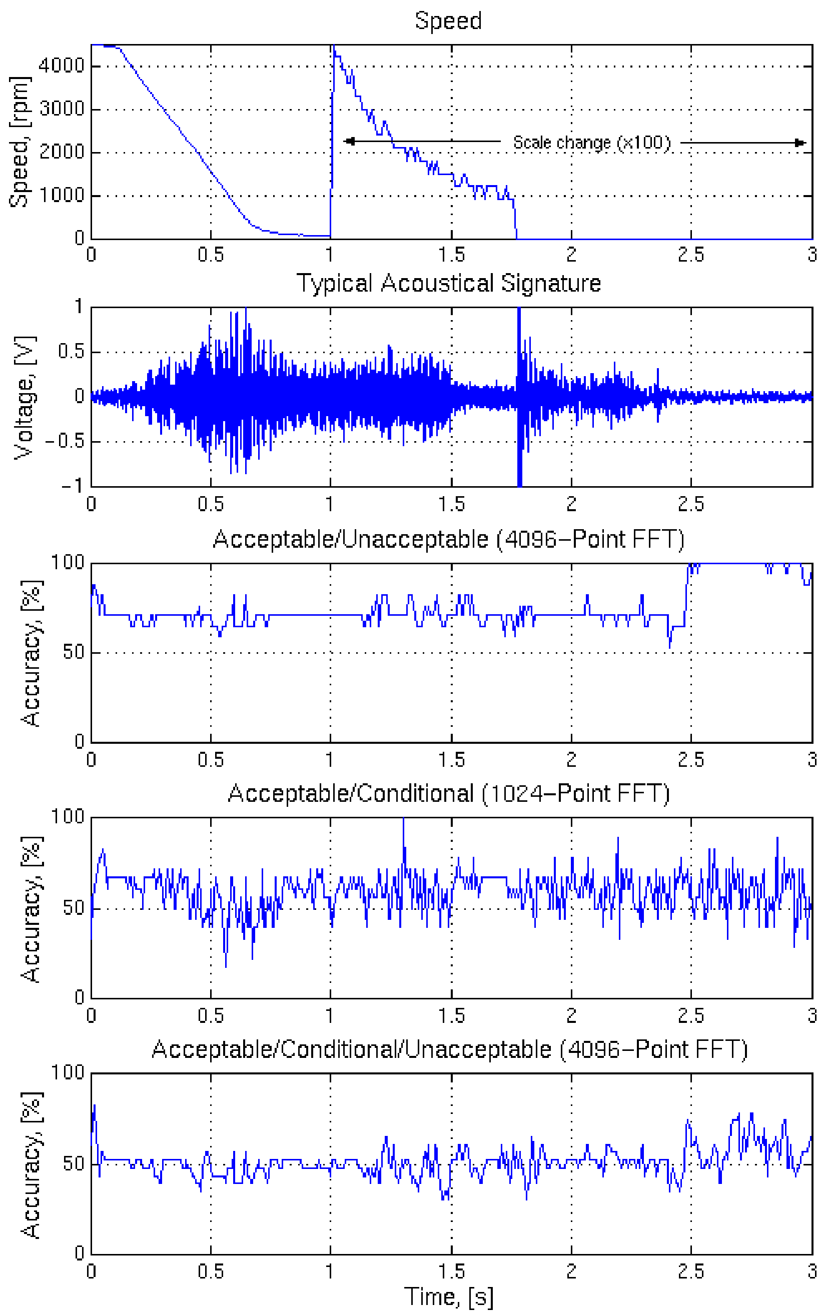

FIGURE 4. Classification accuracy as a function of time (compared with a typical speed and acoustical waveform).

Acceptable and unacceptable bond quality can be reliably detected under most parameter combinations that were investigated. Interestingly, the differences in the Cu's surface preparation was manifested in the acoustical signature at the end of the weld rather than at the beginning.

Acceptable and conditional bond quality was detected but further work needs to be performed to verify and enhance this result. The features for distinguishing between an acceptable and conditional bond appear at a different location within the acoustical signature than they do for an acceptable and unacceptable bond. In particular, conditional bond quality is detected at approximately 1.3 seconds after contact is made between the faying surfaces.

The classification system was unsuccessful at finding three partitions within the data space that could accurately identify and discriminate between the three different bond quality classes. It is possible that the classifier's inability to discriminate between all three classes is due to an insufficient number of training vectors. Furthermore, additional feature analysis techniques and improved learning algorithms might rectify this shortcoming.

CONCLUSIONS AND FUTURE WORK

A bond quality classification system was developed using a novel, non-contact, acoustical emission sensing technique that:

- Identifies features within the acoustical signature of an inertia friction weld that are indicative of the process's ability to produce a quality bond.
- Provides a real-time response with minimal hardware requirements.
- Tolerates noisy and ill-defined data.

Future work includes the following:

- Compare and contrast the non-contact sensing capabilities of this sensor with a piezoelectric transducer that was used by Wang, et al. [3].
- Generate a larger experimental matrix to include contamination conditions (e.g., fingerprints) to freshly machined surfaces.
- Determine the directional characteristics of the sensing ring.
- Investigate other feature extraction methods, such as, wavelets and spectograms.
- Analyze the data with other neural network techniques, such as, an adaptive probabilistic neural network.

ACKNOWLEDGMENTS

This work was conducted at Los Alamos National Laboratory, which is operated by the University of California for the United States Department of Energy under Contract Number W-7405-ENG-36. The authors gratefully acknowledge the assistance of Mr. Paul Martinez and Mr. Dane Knowlton with electronic support, Ms. Ann Kelly with metallographic preparation, and Mr. Ray Dixon for his critical review.

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